Event-Triggered Distributed Multisensor Multitarget Tracking with GM-PHD Filter

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Abstract. This paper focuses on a distributed event-triggered Gaussian mixture probability hypothesis density (GM-PHD) filtering algorithm. In this algorithm, sensors transmit their Gaussian components to neighbors basing on the event-triggered conditions. Then Gaussian components are fused for certain times by matrix reformulation method. This algorithm can reduce data transmission and energy consumption with guaranteeing the estimation performance. Simulation experiment verifies the performance of this algorithm.

Keywords: event-triggered, GM-PHD, matrix reformulation, distributed.

1 Introduction

With the electronic information technology developing rapidly, target tracking technology has become a focus of research in the fields of both civilian and military [1]-[5]. Target tracking technology is proposed in the 1930s, then Wax defines the concept of multitarget tracking (MTT) [5] and initially applies MTT technology to air defense systems.

In the complex tracking environment, tracking the target accurately in real time and shielding the interference of external factors are always the difficulties and key problems in practice. According to different mathematical theories, MTT technology is divided into two classes, namely, tracking strategy based on data association (DA) [6] and random finite sets (RFS) [7].

DA algorithm is limited by the burden of data, computation explosion is easy to appear under the circumstance of tracking targets. Therefore, Mahler proposes the theory of RFS and introduces RFS into MTT technology basing on the Bayesian framework [8]. Compared with the traditional DA algorithm, RFS algorithm bears less DA calculation, and the effectiveness of RFS algorithm is significantly improved.

Since wireless sensor networks are battery-powered, the continuous working time of network is limited [9]. In the environment of electronic warfare, the massive measurement transmission between sensors and their neighbors will increase the possibility of being detected by the enemy and reduce the viability of the network [9]. Due to the uncertain maneuvering characteristics of the target, performing long-time state estimation of the target has some difficulties such as packet loss,intermittent observation, noise interference, and communication network congestion.

In recent years, event-triggered mechanism attracts much attentions from researches [10]-[12]. Such as the method that each sensor node transmits measurement when the mean square error between the latest transmitted estimate value and the current estimated value exceeds the triggered threshold [12]. However, event-triggered MTT is still a problem in the practical application.

In this paper, event-triggered distributed multisensor multitarget tracking is proposed. This algorithm has three innovations:

(1) this paper proposes an event-triggered method, sensors transmit their measurements by (5),

(2) this paper combines the event-triggered method with multisensor MTT to reduce data transmission and energy consumption,

(3) this paper proposes the distributed multisensor MTT algorithm.

The rest of this paper is organized as follows. Section 2 considers some concepts of the considered problem. Section 3 proposes an event-triggered GM-PHD algorithm. In Section 4, a distributed GM-PHD algorithm with event-triggered mechanism is designed. The effectiveness of this algorithm is verified in Section 5 by simulation experiments. This paper is concluded in Section 6.

2 Preliminaries

In the communication network, each sensor can obtain measurement of multitarget and communicate with its neighbor nodes.

2.1 The communication topology

Undirected graph $G = (v, \varepsilon)$ represents the communication topology of the sensor network, where $v = \{1, 2, \ldots, L\}$ corresponds to the set of sensors, ε corresponds to the communication channel between sensor nodes. In the undirected graph, if $(i, j) \in \varepsilon$ exists, then $(j, i) \in \varepsilon$ exists, which means nodes i and j are neighbor nodes and can transmit information with each other. The neighbor nodes of node l are represented as set $\{l' \in v \mid (l', l) \in \varepsilon\}$,which has L_l nodes.

2.2 Problem formulation

Consider a linear Gaussian form as

$$f_{k|k-1}(x_k \mid x_{k-1}) = N(x_k; F_{k-1}x_{k-1}, Q_{k-1}),$$

$$\varphi_k(z_k \mid x_k) = N(z_k; H_k x_k, R_k),$$

where z_k is the measurement of sensor at time instant k , x_k is the target state. R_k and Q_{k-1} are covariance matrices of measurement noise and process noise, respectively. H_k and F_{k-1} are the measurement matrix and the state transition matrix, respectively.

2.3 GM-PHD filter algorithm

GM-PHD filtering algorithm is described by the following five steps.

Step 1. Initialization

At time instant $k = 0$, the Gaussian mixture form is initialized to the initial state transformed from the initial measurement $Z_0 = \left\{z_0^{(1)}, \ldots, z_0^{(l)}\right\}$.

$$V_0(x_0) = \sum_{i=1}^{J_0} w_0^i N(x_0; m_0^i, P_0^i) \cdot$$

where J_0 is the number of the Gaussian components in $V_0(x_0)$, w_0^i , m_0^i and P_0^i are the weight, mean value and covariance of the Gaussian components in $V_0(x_0)$, respectively.

Step 2. Prediction

Suppose the Gaussian mixture form of the updated intensity at time instant $k-1$ is

$$V_{k-1}(x_{k-1}) = \sum_{i=1}^{J_{k-1}} w_{k-1}^i N(x_{k-1}; m_{k-1}^i, P_{k-1}^i) . \tag{1}$$

Then the Gaussian mixture form of the predicted intensity at time instant k is

$$\begin{aligned} V_{k|k-1}(x_k) &= V_{S,k|k-1}(x_k) + \gamma_k(x_k) + V_{\beta,k|k-1}(x_k) \\ &= \sum_{i=1}^{J_{k|k-1}} w_{k|k-1}^i N(x_k; m_{k|k-1}^i, P_{k|k-1}^i), \end{aligned} \tag{2}$$

where $V_{S,k|k-1}(x_k)$ is the survival target intensity, $\gamma_k(x_k)$ is the intensity functions of the birth RFS, $V_{\beta,k|k-1}(x_k)$ is the spawn target intensity.

Step 3. Update

Let the Gaussian mixture form after prediction at time instant k is (2), Then, the posterior target intensity at time instant k can be obtained by

$$V_k(x_k;z) = (1-p_{D,k})V_{k|k-1}(x_k) + \sum_{j=1}^{J_{k|k-1}} w_k^j N(x_k; m_k^j, P_k^j), \tag{3}$$

where $(1-p_{D,k})V_{k|k-1}(x_k)$ is the missed target intensity, and $\sum_{j=1}^{J_{k|k-1}} w_k^j N(x_k; m_k^j, P_k^j)$ is the detected target intensity. $p_{D,k}$ is the detection probability.

Step 4. Truncating and merging of Gaussian components

According to [13], if $U = [u^{ij}]$ is a $A \times B$ matrix, define $[u^{ij}]^{\oplus}_{A\times B} \triangleq \sum_{i=1}^{A}\sum_{j=1}^{B} u^{ij}$.

Then, (3) can be reformulated as $V_k(x_k;z) = [u_k^{i0}]^{\oplus}_{J_{k|k-1}\times 1} + [u_k^{ij}]^{\oplus}_{J_{k|k-1}\times M_k}$, where M_k is the dimension of the vectors in the set of measurement $Z_k = \{z_{k,1},\ldots,z_{k,M_k}\}$, the corresponding weight matrix W_k of $[u_k^{i0}]^{\oplus}_{J_{k|k-1}\times 1} + [u_k^{ij}]^{\oplus}_{J_{k|k-1}\times M_k}$ can be expressed as

$$\begin{array}{cc} \begin{bmatrix} w_k^{10} \\ \vdots \\ w_k^{J_{k|k-1}0} \end{bmatrix} + & \begin{bmatrix} w_k^{11} & w_k^{12} & \cdots & w_k^{1j} & \cdots & w_k^{1M_k} \\ \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ w_k^{J_{k|k-1}1} & w_k^{J_{k|k-1}2} & \cdots & w_k^{J_{k|k-1}j} & \cdots & w_k^{J_{k|k-1}M_k} \end{bmatrix} \\ & \begin{matrix} z_{k,1} & z_{k,2} & \cdots & z_{k,j} & \cdots & z_{k,M_k} \end{matrix} \end{array} \tag{4}$$

The weight in (4) means the probability that the corresponding component in $[u_k^{i0}]^{\oplus}_{J_{k|k-1}\times 1} + [u_k^{ij}]^{\oplus}_{J_{k|k-1}\times M_k}$ is the target. The weights of W_k in the same row come from the same component, and the weights of $[u_k^{ij}]^{\oplus}_{J_{k|k-1}\times M_k}$ in the same column come from the same measurement.

The process of truncating and merging for Gaussian components of the single sensor is divided into two steps. First, the Gaussian component is truncated and the truncation threshold T_{th} is set to make the weight in $[u_k^{ij}]^{\oplus}_{J_{k|k-1}\times M_k}$ satisfies

$$\overline{w}_k^{ij} = \begin{cases} w_k^{ij},\ w_k^{ij} > T_{th}, \\ 0\ ,\ otherwise. \end{cases} \tag{5}$$

Then, the Gaussian components of $[u_k^{ij}]^{\oplus}_{J_{k|k-1}\times M_k}$ in the same column are merged according to the steps in Algorithm 1 given below.

Algorithm 1: Merging algorithm for single sensor GM-PHD filter.

For $j = 1,\ldots,M_k$, do

(1) The biggest weight of the Gaussian components in the j th column is $\overline{w}_k^{\pi_i j}$, $\pi_i = \arg\max_{1 \le i \le J_{k|k-1}} \overline{w}_k^{ij}$, the corresponding Gaussian component is $u_k^{\pi_i j}$;

(2) The set of the Gaussian component which is close to $u_k^{\pi_i j}$ in the j th column is $u_k^{\Omega_i j}$, $\Omega_i = \{ i \mid (m_k^{\pi_i j} - m_k^{ij})^T (P_k^{ij})^{-1} (m_k^{\pi_i j} - m_k^{ij}) \le Y,\ 1 \le i \le J_{k|k-1} \}$, where Y is the merging threshold for single sensor;

(3) The weight, mean value and convariance of the Gaussian component merged by $u_k^{\pi_i j}$ and $u_k^{\Omega_i j}$ are $\tilde{w}_k^{\pi_i j} = \sum_{i \in \Omega_i} \overline{w}_k^{ij}$, $\tilde{m}_k^{\pi_i j} = \frac{1}{\tilde{w}_k^{\pi_i j}} \sum_{i \in \Omega_i} \overline{w}_k^{ij} m_k^{ij}$ and $\tilde{P}_k^{\pi_i j} = \sum_{i \in \Omega_i} \left(\frac{\overline{w}_k^{ij}}{\tilde{w}_k^{\pi_i j}} \right)^2 (P_k^{ij} + (m_k^{\pi_i j} - m_k^{ij})(m_k^{\pi_i j} - m_k^{ij})^T)$, respectively, $\tilde{w}_k^{ij} = 0,\ i \in \Omega_i$.

Step 5. State estimation

The number of targets $\hat{N}_k$ is the sum of weights which is obtained by

$$\hat{N}_k = \sum_{i=1}^{J_{k|k-1}} \tilde{w}_k^{ij} . \tag{6}$$

The estimated value of each target state is the mean value of the Gaussian component which satisfies

$$\tilde{w}_k^{ij} \ge 0.5 . \tag{7}$$

3 Event-triggered GM-PHD algorithm

In order to reduce data transmission and energy consumption, this section proposes the event-triggered GM-PHD algorithm.

$F = \{f_1, ..., f_a\}$ is a set with a vectors, $S = \{s_1, ..., s_b\}$ is a set with b vectors, then we define $\overline{F} = [f_1, ..., f_a]$ and $\overline{S} = [s_1, ..., s_b]$ are matrices consisted by vectors in F and S, respectively. When $a \ne b$, add a $|a-b|$-dimensional zero matrix to the matrix with smaller dimension to equate the dimensions of two matrices, then perform $\overline{F} - \overline{S}$.

At each time instant k, whether sensor l uses the current measurement to perform the update step depends on the following event-triggered mechanism:

$$\delta_k^l = \begin{cases} 1, if\,(\overline{Z}_{\tau_{k-1}}^l - \overline{Z}_k)(\overline{Z}_{\tau_{k-1}}^l - \overline{Z}_k)^T > \delta_{2\times 2}, \\ 0,\ otherwise, \end{cases} \tag{8}$$

where the time instant τ_{k-1} is the last time instant of transmitting the measurement set by sensor l, $Z_{\tau_{k-1}}^l = \{ z_{\tau_{k-1},1}^l, z_{\tau_{k-1},2}^l, ..., z_{\tau_{k-1},M_{\tau_{k-1}}}^l \}$ is the measurement set of sensor l at time instant τ_{k-1}, $Z_k^l = \{z_{k,1}^l, z_{k,2}^l, \ldots, z_{k,M_k}^l\}$ is the latest measurement set of sensor l, $\delta_{2\times 2} = \begin{bmatrix} a_1 & a_2 \\ a_2 & a_3 \end{bmatrix}$ is the triggered threshold, where $a_1 \geq 0,\ a_3 \geq 0$, a_2 is a sufficiently small scalar that has no influence on triggering.

When δ_k^l is set to 1, sensor l uses the current measurement at time instant k to complete the update step. When δ_k^l is set to 0, sensor performs subsequent calculations basing on the measurement at time instant τ_{k-1}.

4 Event-triggered distributed multisensor multitarget tracking with GM-PHD filter

After truncating and merging for single sensor tracking in section 2.3, the weight matrix of $[\tilde{u}_k^{i0}]^{\oplus}_{J_{k|k-1}\times 1} + [\tilde{u}_k^{ij}]^{\oplus}_{J_{k|k-1}\times \sum_{l=1}^{L_l+1} M_k^l}$ formed by the Gaussian components of L_l+1 sensors (sensor l and neighbors) is

$$\begin{bmatrix} \tilde{w}_k^{10} \\ \vdots \\ \tilde{w}_k^{J_{k|k-1}0} \end{bmatrix} + \begin{array}{c} \begin{bmatrix} \tilde{w}_{k,1}^{11} & \tilde{w}_{k,1}^{12} & \cdots & \tilde{w}_{k,1}^{1j} & \cdots & \tilde{w}_{k,1}^{1M_k^1} & \cdots & \tilde{w}_{k,L_l+1}^{11} & \tilde{w}_{k,L_l+1}^{12} & \cdots & \tilde{w}_{k,L_l+1}^{1j} & \cdots & \tilde{w}_{k,L_l+1}^{1M_k^{L_l+1}} \\ \vdots & \cdots & \vdots & \vdots & \cdots & \vdots & \cdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ \tilde{w}_{k,1}^{J_{k|k-1}1} & \tilde{w}_{k,1}^{J_{k|k-1}2} & \cdots & \tilde{w}_{k,1}^{J_{k|k-1}j} & \cdots & \tilde{w}_{k,1}^{J_{k|k-1}M_k^1} & \cdots & \tilde{w}_{k,L_l+1}^{J_{k|k-1}1} & \tilde{w}_{k,L_l+1}^{J_{k|k-1}2} & \cdots & \tilde{w}_{k,L_l+1}^{J_{k|k-1}j} & \cdots & \tilde{w}_{k,L_l+1}^{J_{k|k-1}M_k^{L_l+1}} \end{bmatrix} \\ \begin{matrix} z_{k,1}^1 & z_{k,2}^1 & \cdots & z_{k,j}^1 & \cdots & z_{k,M_k^1}^1 & \cdots & z_{k,1}^{L_l+1} & z_{k,2}^{L_l+1} & \cdots & z_{k,j}^{L_l+1} & \cdots & z_{k,M_k^{L_l+1}}^{L_l+1} \end{matrix} \end{array}$$

Multisensor GM-PHD filter fusion could be achieved by combining the Gaussian component in the same row. Merging algorithm for multisensor GM-PHD filter can be achieved according to the steps in Algorithm 2 given below.

Algorithm 2: Merging algorithm for multisensor GM-PHD filter.

For $i = 1, \ldots, J_{k|k-1}$, do

(1) The biggest weight of the Gaussian components in the i th row is $\tilde{w}_k^{i\tilde{\pi}_j}$, $\tilde{\pi}_j = \underset{1\leq j\leq \sum_{l=1}^{L_l+1} M_k^l}{\arg\max}\ \tilde{w}_k^{ij}$, the corresponding Gaussian component is $\tilde{u}_k^{i\tilde{\pi}_j}$;

(2) The set of the Gaussian component which is close to $\tilde{u}_k^{i\tilde{\pi}_j}$ in the i th row is $\tilde{u}_k^{i\tilde{\Omega}_j}$, $\tilde{\Omega}_j = \{ j \mid (\tilde{m}_k^{i\tilde{\pi}_j} - \tilde{m}_k^{ij})^T (\tilde{P}_k^{ij} + \tilde{P}_k^{i\pi_j})^{-1} (\tilde{m}_k^{i\pi_j} - \tilde{m}_k^{ij}) \leq \tilde{Y},\ 1 \leq j \leq \sum_{l=1}^{L_l+1} M_k^l \}$, where $\tilde{Y}$ is the merging threshold for multisensor;

(3) The weight, mean value and convariance of the Gaussian component merged by $\tilde{u}_k^{i\tilde{\pi}_j}$ and $\tilde{u}_k^{i\tilde{\Omega}_j}$ are $\hat{w}_k^{i\tilde{\pi}_j} = 1 - \prod_{j\in\tilde{\Omega}_j} (1 - \tilde{w}_k^{ij})$, $\hat{m}_k^{i\tilde{\pi}_j} = \sum_{j\in\tilde{\Omega}_j} (\tilde{w}_k^{ij} / \sum_{j\in\tilde{\Omega}_j} \tilde{w}_k^{ij}) \tilde{m}_k^{ij}$ and

$\hat{P}_k^{i\tilde{\pi}_j} = \sum_{j\in\tilde{\Omega}_j} (\tilde{w}_k^{ij} / \sum_{j\in\tilde{\Omega}_j} \tilde{w}_k^{ij})^2 (\tilde{P}_k^{ij} + (\tilde{m}_k^{ij} - \tilde{m}_k^{i\tilde{\pi}_j})(\tilde{m}_k^{ij} - \tilde{m}_k^{i\tilde{\pi}_j})^T)$, respectively;

(4) Remove $\tilde{u}_k^{i\tilde{\pi}_j}$ and $\tilde{u}_k^{i\tilde{\Omega}_j}$ from row i, repeat (1), (2), (3) steps until row i becomes empty.

Algorithm 3 summarizes the process of the event-triggered distributed multisensor MTT with GM-PHD algorithm in this paper.

Algorithm 3: Event-triggered distributed multisensor MTT with GM-PHD filter

Part A: Local estimation for each node $l \in V$ at time instant k.

(1) Predict using (1), (2).

(2) Update the local state and $w_k^{l,ij}$, $m_k^{l,ij}$, $P_k^{l,ij}$ through (3).

(3) Truncating and merging of Gaussian components using (5) and Algorithm 1, get $\tilde{w}_k^{l,ij}$, $\tilde{m}_k^{l,ij}$, $\tilde{P}_k^{l,ij}$.

Part B: Distributed multisensor multitarget tracking basing on neighbor nodes.

(4) Intialize the algorithm, $\widehat{w}_{k,0}^{l,ij} = \tilde{w}_k^{l,ij}$, $\widehat{m}_{k,0}^{l,ij} = \tilde{m}_k^{l,ij}$, $\widehat{P}_{k,0}^{l,ij} = \tilde{P}_k^{l,ij}$.

(5) Communicate the information pair $(\widehat{w}_k^{l,ij}, \widehat{m}_k^{l,ij}, \widehat{P}_k^{l,ij})$ with neighbors.

(6) Fuse the information using Algorithm 2, get $(\hat{w}_k^{l,ij}, \hat{m}_k^{l,ij}, \hat{P}_k^{l,ij})$.

(7) Repeat updating the estimates for C (C is the number of iterations) iterations until the difference between the estimates of neighbors is less than the predetermined difference, $\widehat{w}_{k,C}^{l,ij} = \hat{w}_k^{l,ij}$, $\widehat{m}_{k,C}^{l,ij} = \hat{m}_k^{l,ij}$, $\widehat{P}_{k,C}^{l,ij} = \hat{P}_k^{l,ij}$.

(8) Obtain the set of state estimation X_k consisted by $\widehat{m}_{k,C}^{l,ij}$ according to (6), (7).

(9) Output: X_k.

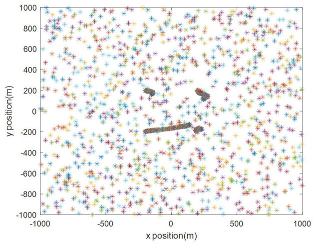
5 Numerical results and analysis

5.1 The simulation scene

The tracking environment is set as the detection area of $[-1000,1000](m)\times[-1000,1000](m)$ in the two-dimensional space. Suppose $x_k = \{x_{k,1}, x_{k,2}, x_{k,3}, x_{k,4}\}^T$ represents the target state at time instant k, where $\{x_{k,1}, x_{k,3}\}^T$ represents the target position and $\{x_{k,2}, x_{k,4}\}^T$ represents the speed. The simulation time of this algorithm is 100s, sampling interval T is 1s, the target state equation and observation equation are $z_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} x_k + v_k$ and $x_k = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} x_{k-1} + \begin{bmatrix} T^2/2 & 0 \\ 0 & T^2/2 \\ T & 0 \\ 0 & T \end{bmatrix} v'_k$.

The measurement noise and process noise belong to white Gaussian noise, represented as v_k and v'_k, with mean values equal to 0, and their covariance matrices are $Q_v = diag([0.5, 0.5])$ and $Q_{v'} = diag([0.5, 0.5])$. In the experiment, detection probability is $pd = 0.99$, survival probability is $ps = 0.98$, truncation threshold is $T_{th} = 10^{-7}$, merge threshold is $\mathrm{U} = 1$.

As shown in Fig.1, the two-dimensional space contains the trajectories and measurements of the four targets in the whole detection process, where the number of clutter follows Poisson distribution and the mean value $\lambda = 3$. The simulation environment includes two surviving targets, a spawn target and a newborn target, and the covariance matrix of both targets is $P = diag(1, 2, 1, 2)$.



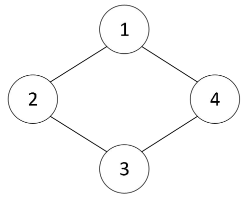


Fig1. Measurement **Fig2.** Topological relationship

A wireless sensor network consisted of four sensor nodes is established, and the topological relationship is shown in Fig 2.

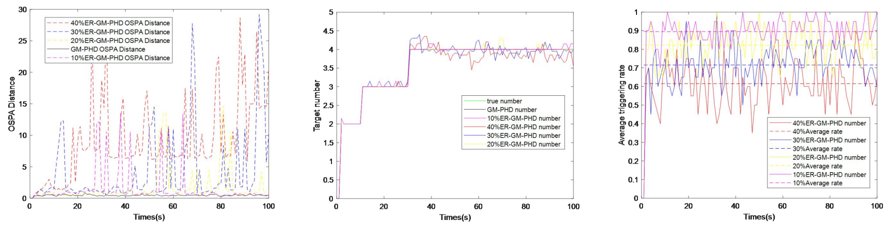
5.2 Event-Triggered Performance

Note that all the results presented in this section are averages from 30 separate Monte Carlo runs. The performance of this algorithm is tested at different average trigger rates (i.e. 90%, 80%, 70% and 60%). Different triggered thresholds correspond to different average trigger rate, as shown in Table 1.

Table 1. Triggered thresholds and triggered rate

Triggered rate	Thresholds
90%	a_1=4.0, a_3=4.0
80%	a_1=6.0, a_3=6.0
70%	a_1=8.5, a_3=8.5
60%	a_1=10.5, a_3=10.5

In order to save energy consumption, set the number of iterations to 1, then the average OSPA distance (m) (with $p = 2$ and $c = 150$) at average triggered rate, the average number of detected targets at average triggered rate and the average triggered rate of detected targets at 90%, 80%, 70% and 60% are presented in Fig. 3 as follows.



(a) Average OSPA distance (b) Average number (c) Average triggered rate

Fig3. The simulation results at average triggered rate: 90%, 80%, 70% and 60%

It can be shown in Fig. 3 that all the algorithms considered have a certain delay in detecting the newly emerging target. OSPA also increases when the number of targets changes and the triggered rate decreases. It can be verified that this algorithm can reduce data transmission significantly

6 Conclusions

This paper proposed the event-triggered distributed multisensor MTT algorithm with the GM-PHD filter. By using the event-triggered communication scheme, the communication consumption from sensor to neighbors could be reduced significantly. The relationship between communication rate and tracking performance could be balanced by appropriately adjusting the triggered threshold. Finally, simulation evaluated the effectiveness of this algorithm by applying it to multisensor MTT. Future work will concern improving the performance of event-triggered MTT mechanism and proving its stability.

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